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The effect of information from dash-based human-machine interfaces on drivers' gaze patterns and lane-change manoeuvres after conditionally automated driving

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ABSTRACT

The goal of this paper was to measure the effect of Human-Machine Interface (HMI) information and guidance on drivers' gaze and takeover behaviour during transitions of control from automation. The motivation for this study came from a gap in the literature, where previous research reports improved performance of drivers' takeover based on HMI information, without considering its effect on drivers' visual attention distribution, and how drivers also use the information available in the environment to guide their response. This driving simulator study investigated drivers' lane-changing behaviour after resumption of control from automation. Different levels of information were provided on a dash-based HMI, prior to each lane change, to investigate how drivers distribute their attention between the surrounding environment and the HMI. The difficulty of the lane change was also manipulated by controlling the position of approaching vehicles in drivers' offside lane. Results indicated that drivers' decision-making time was sensitive to the presence of nearby vehicles in the offside lane, but not directly influenced by the information on the HMI. In terms of gaze behaviour, the closer the position of vehicles in the offside lane, the longer drivers looked in that direction. Drivers looked more at the HMI, and less towards the road centre, when the HMI presented information about automation status, and included an advisory message indicating it was safe to change lane. Machine learning techniques showed a strong relationship between drivers' gaze to the information presented on the HMI, and decision-making time (DMT). These results contribute to our understanding of HMI design for automated vehicles, by demonstrating the attentional costs of an overly-informative HMI, and that drivers still rely on environmental information to perform a lane-change, even when the same information can be acquired by the HMI of the vehicle.

1. Introduction

Vehicle automation, which partially supplants the moment to moment physical control and monitoring of the driving task by humans, is an increasing feature in new vehicles. The implementation of such systems could bring several benefits (Fagnant & Kockelman, 2015), including the extension of driving and personal mobility to impaired or older drivers (Young & Bunce, 2011), or reducing driver-workload, for example, by taking control of monotonous driving tasks (e.g. engaging adaptive cruise control systems in traffic jam and car-following scenarios, see Stanton & Young, 1998).

Despite its promised capabilities, current vehicle automation technology still has a limited Operational Design Domain (ODD), which, when exceeded, requires the human to take over control (NHTSA, 2016). However, there is growing evidence that removing drivers from the decision-making and physical control loops (Louw et al., 2015; Merat et al., 2019) may lead to a loss of situation awareness (see Endsley, 1995), and impaired perceptual-motor coordination (Wilkie & Wann, 2010), which are both required to safely resume control of the driving task after automation (Damböck et al., 2013; Mole et al., 2019).

One example of a manoeuvre that could be coupled with a transition of control to manual driving is a lane change manoeuvre, which can be challenging, even during manual driving, due to the complexities associated with determining the correct time to change lane, especially in

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heavy traffic (Gipps, 1986). Previous literature presents an extensive list of theoretical and mechanistic models that consider a wide range of factors that influence a lane-change decision, and its subsequent outcomes (for more details, see a systematic literature review on this topic by Zheng (2014); and the integrated Lane-Change decision modelling framework, developed by Ali et al., 2021). For instance, Arbis & Dixit (2019) developed a game-theoretical utility model for lane changes, and concluded that the probability of decision conflicts (i.e. increased decision uncertainty, as defined by Shaw, 1982) is directly affected by the characteristics of the traffic environment, such as the proximity of the upcoming vehicles in the adjacent lane. This argument suggests that the challenges imposed by the nature of a lane-change task may already stress drivers' cognitive resources, and this process can be aggravated by automation, if combined with a transition of control.

Results from previous empirical studies in automation support the idea that the introduction of a transition of control during a lane-change scenario can compromise drivers' ability to change lanes safely, and effectively. For example, Madigan et al. (2017) reported that, compared to manual driving, drivers in partial automation took longer to overtake a lead vehicle, whenever a transition of control was required, resulting in shorter minimum headway distances to the lead vehicle. This delayed response was considered to be due to the need for drivers to understand both system behaviour and road conditions, after a transition of control, before overtaking the lead vehicle.

A large body of literature has investigated how supportive information provided by a Human-Machine Interface (HMI) can support drivers during a lane-changing task. In the context of vehicle automation, a number of studies have shown that providing drivers with system-related information via the HMI can support their understanding of the system's behaviour, promoting safer transitions of control (Saffarian et al., 2012; Gonçalves et al., 2017, Stockert et al., 2015; Banks & Stanton, 2016). In-vehicle HMI can be used to provide automation-related messages, as well as information about the road environment, minimising a driver's need to scan their surroundings, to aid with situation awareness recovery, after a transition of control. Several studies (Richardson et al., 2018; Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2014) have reported that drivers react faster, and more accurately, to takeover requests from automation, when they receive guidance from the vehicle HMI about the surrounding traffic conditions, prior to a takeover.

When it comes to manual lane-change scenarios, Hofmann et al. (2010) report that providing drivers with information about the direction of travel, and the number of lanes to be crossed, in advance of a lane-changing manoeuvre, reduced reaction time to the lane change, accompanied by lower lateral accelerations. Using a linear mixed model on driving simulator data, Ali et al. (2020) demonstrated that supportive information from connected vehicles in the surrounding environment led to safer transitions, with higher time-to-collision and a smoother acceleration profile, compared to the non-assisted lane-change manoeuvres. These studies provide strong evidence that supportive information from HMI may significantly improve lane-change safety in manual driving. However, less is known about how additional information assists lane changes that are required after takeover from automation.

The majority of the studies reported above base their conclusions either on analyses of drivers' subjective responses, in terms of acceptance/perceived usability of the system (Richardson et al., 2018; Körber et al., 2018; Beller et al., 2013), or vehicle-based metrics, such as reaction time, and time to collision (Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2014; Ali et al., 2021; Ali et al., 2020; Arbis & Dixit, 2019). Regardless of the undeniable contribution of these studies, their approach fails to address how decision-making by drivers, in terms of the processing and acquisition of visual information, is affected by the introduction of additional guidance from an HMI, either with respect to automation status, or in terms of the behaviour of surrounding traffic. Ali et al. (2020) found that the use of information about the surrounding environment in the vehicle's HMI significantly changes the way drivers deal with a lane-change task. Additionally, using a drift–diffusion model, Forstmann et al. (2016) demonstrated that the sequence in which humans sample visual information significantly affects the way they make a decision, in terms of decision time, choice selection, and ratio of correct responses. However, it is still unclear how additional visual information from an HMI affects drivers' information processing during a lane change manoeuvre which follows a transition of control from automation.

Research shows a good correlation between the duration of eye gaze to a particular task, and the level of dedicated visual attention (Carrasco, 2011; Posner, 1980). Studies have found that both covert attention and gaze are sensitive to context-specific stimuli, meaning that eye movements are generally drawn towards the visual elements of any stimulus demanding one's attention, at a given moment (Borji & Itti, 2013). Longer gaze times towards a given element are, therefore, generally used as a proxy for human information processing.

Using a simulated car-following study, Sullivan et al. (2012) demonstrated that, during moments of high uncertainty, drivers looked more frequently towards locations with valuable information about the task in hand, such as the speedometer. A *meta*-analytical literature review by Orquin and Mueller Loose (2013), demonstrated that eye movements have a co-causal relation with human decision-making, with humans fixating more on the information that supports the decision they are about to make. This assumption was further supported by the models reported in Krajbich et al. (2012), which were able to predict the decision-maker's choice, and response time, based on the way they distributed their gaze between the different sources of visual information. Therefore, one can argue that, in order to understand how drivers process information when conducting a demanding task immediately after resuming control from automation (such as a lane change), it is important to understand where they direct their gaze at each stage of this process.

In a previous study (Gonçalves et al., 2020), we observed that, during an automated lane change, drivers presented the same general pattern of eye movements as those reported in studies involving a manual lane change (Tijerina et al., 2005; Salvucci et al., 2001). However, our results also showed a significant increase in drivers' vertical gaze dispersion during automated lane changing, with more glances towards the vehicle's HMI, which was placed in the dashboard area, and displayed the automation status (on/off). Our results also indicated that when the same information could be obtained by looking at the road, as compared to looking at the HMI, drivers tended to look more at the road environment, relying less on the HMI. As our previous studies did not systematically control the information given to drivers during the transition of control, it is not currently clear how drivers' gaze is influenced by the information provided by the system's HMI, in such lane-changing tasks.

1.1. Current study

The study reported in this paper was funded by the European project AdaptIVe (Grant Agreement No. 610428). Its main objective was to evaluate the impact of different types of information, provided by an automated vehicle's HMI, on drivers' gaze behaviour, and their resumption of control in preparation for a lane-change manoeuvre, immediately after L3 automation (SAE, 2018). In particular, we investigated how HMI messages about system status, presence of traffic in the adjacent lane, and the presence of a guiding arrow advising drivers about whether it was safe to change lane, affected drivers' gaze behaviour and decision-making time during a lane change. The following research questions were investigated:

1. How does the type of information presented on the HMI of an automated system affect drivers' gaze behaviour before changing lane, following a request to take over from vehicle automation?

2. How does the information provided on an HMI affect when drivers begin to change lane?
3. Does the density of the surrounding traffic (e.g. presence of traffic in the adjacent lane) affect drivers' reliance on the system HMI?

Based on previous literature (Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2014, Stockert et al., 2015), it was hypothesised that drivers would react faster in a given scenario, if information about the system status and surrounding traffic were available via the HMI during the transition. This help from the HMI was expected to be more evident for more challenging decision-making scenarios (higher traffic density), since it was hypothesised that giving drivers more guidance would reduce their uncertainty and decision-making time (Ali et al., 2020). Based on our previous study (Gonçalves et al., 2020), we expected that drivers would have increased gaze towards the information on the HMI, to check the system status immediately after the transition of control (whenever present), but not necessarily rely as much on the information about the road environment (a guiding green arrow). The presence of vehicles in the adjacent lane was hypothesized to increase the frequency of drivers' gaze to the side mirrors, and to the HMI, whenever information about the surrounding traffic was displayed by the system (Tijerina et al., 2005).

2. Method

2.1. Participants

Thirty drivers (17 male, 13 female), aged between 21 and 60 years (M = 35.53, SD = 11.51) were recruited via the participant database of the University of Leeds Driving Simulator (UoLDS), and an invitation shared using social media. Participants had normal, or corrected-to-normal, vision, and held a U.K. driving licence for at least two years (M = 13.51, SD = 11.17). Ethical approval was provided by the University of Leeds Ethics committee (Ethics no. LTTRAN-054), and participants received £25 for taking part in the study, which took around 2.5 h to complete.

2.2. Materials

The experiment was conducted at the University of Leeds Driving Simulator (UoLDS). The simulator consists of a 4 m projection dome with 300° projection angle and an 8 degree of freedom motion system. Inside the dome, a Jaguar S-Type cabin with fully operational controls is installed. The Seeing Machines FaceLab v4.5 eye-tracking device was used to record the participants' eye movements, with an update rate of 60 Hz. Inside the simulator's vehicle cabin, a Liliput 7″ VGA touchscreen with 800X480 resolution, was installed near the gear shift, and used for a non-driving related, secondary task, described below. See Fig. 1 for a representation of the experimental set-up.

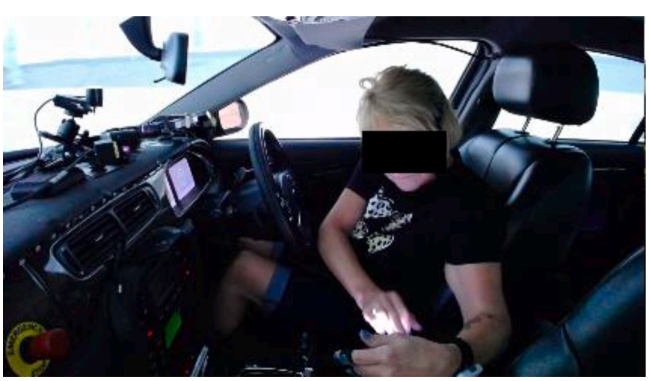

Fig. 1. Representation of the experimental set-up in the University of Leeds Driving Simulator. In this picture, an anonymous experiment participant is driving in automation mode while interacting with the secondary task, presented on the VGA touchscreen. The cameras near the windshield are part of the eye-tracking system.

2.3. Experimental design

Each experimental drive contained six separate scenarios in a continuous drive. Each scenario consisted of an automated car-following task, where drivers needed to disengage the automation to perform a discretionary lane change (as defined by Ali et al., 2020), to overtake any slower lead vehicles. A 3X3 repeated measures design was used, with HMI design (No HMI, System HMI, Full HMI), and distance of vehicles on the offside lane during the lane-change manoeuvre (100 m, 25 m, 15 m), as within-participant factors. Each participant completed three drives (one for each type of HMI), presented in a counterbalanced order.

2.4. Automated driving system

The participant's vehicle was equipped with an automated driving system (SAE level 3; SAE, 2018), which kept the vehicle in the middle of the centre lane, and at a minimum headway of 2 s from the lead vehicle. To activate automation, drivers pulled the right-hand stalk when the vehicle reached 70 mph (speed limit) and was positioned in the centre of the middle lane. The automation could be deactivated by either braking/accelerating, turning the steering wheel more than 2° in either direction, or pulling the same stalk used to turn it on. The system was not able to change lanes by itself. Therefore, participants needed to disengage the automation, perform the manoeuvre manually, and then reengage the system.

2.5. The distance of vehicles in the offside lane

Each lane change was accompanied by a vehicle in the offside lane, which was driving in the same direction as the ego-vehicle (downstream direction), positioned at three different distances: 100 m, 25 m, and 15 m away from the ego vehicle. Each drive contained two repetitions of these distances, presented in a randomised order (see Fig. 2). Different combinations of offside distance were tested in pilot studies, and the most suitable set of variables was selected, to suit the needs of this study. Varying the vehicle's distance in the offside lane was used to simulate higher traffic density, and manipulate the challenges associated with changing lanes. Previous studies have shown that a reduced gap between the ego vehicle and the vehicle in the offside lane increases the uncertainty associated with the lane-change task (as defined by Shaw, 1982), and increases task complexity, thus affecting decision-making time (Gipps, 1986; Ahmed et al., 1996; Arbis & Dixit, 2019). This set-up also allowed us to establish if the provision of guidance information by an HMI (that it was safe to change lane) affected drivers' decisions, and whether this was the same for the three vehicle distances (as observed in Ali et al., 2020).

2.6. HMI configurations

To understand how drivers' decision-making processes, and gaze behaviours, are affected by information about automation status, and the surrounding environment provided by the automation's HMI, three configurations of HMI design were developed. The visual elements of the HMIs were designed by a project partner, CRF (Centro Ricerche Fiat, FIAT,2021). The **No HMI Condition** contained a blank central cluster, with no information on the system's HMI. There was just a short auditory "beep" which informed drivers when the system was turned on/off. A verbal message, played through the car's speakers, informed the driver when the automation was available. The **System HMI Condition**, outlined in Fig. 3, included four screens, which informed the driver that the system was on, off, ready and disengaged.

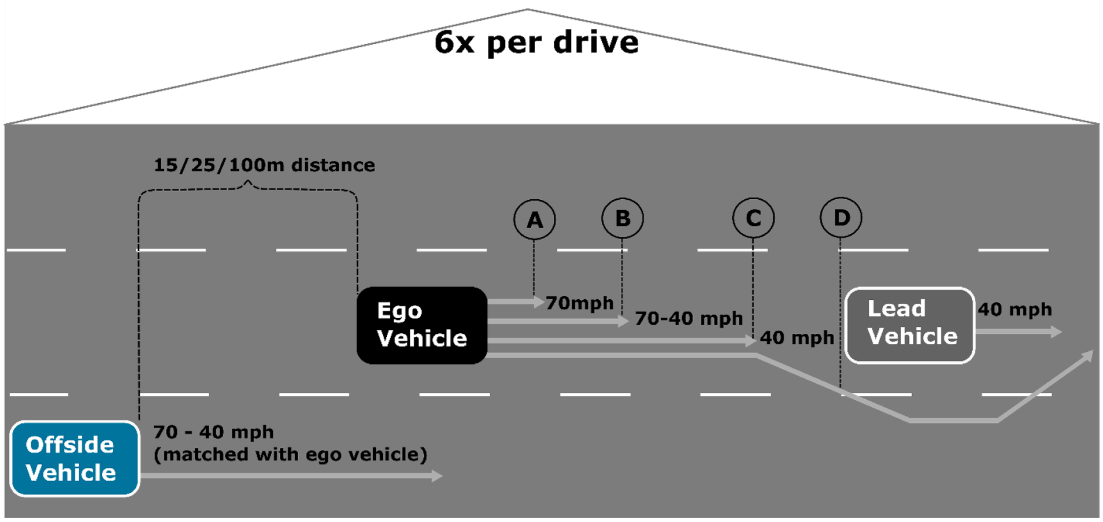

Fig. 2. Representation of the experimental scenario. The schematic depicts one of the six overtaking events that occurred per run. Letters A-D represent the stages of the ego vehicle position and automation state. (A) automated system detects the lead vehicle, (B) automated system starts reducing its speed, to match with the lead vehicle, (C) drivers disengage the automation to perform a manual lane change (variable), and (D) drivers' front tyres crossed the lane markings.

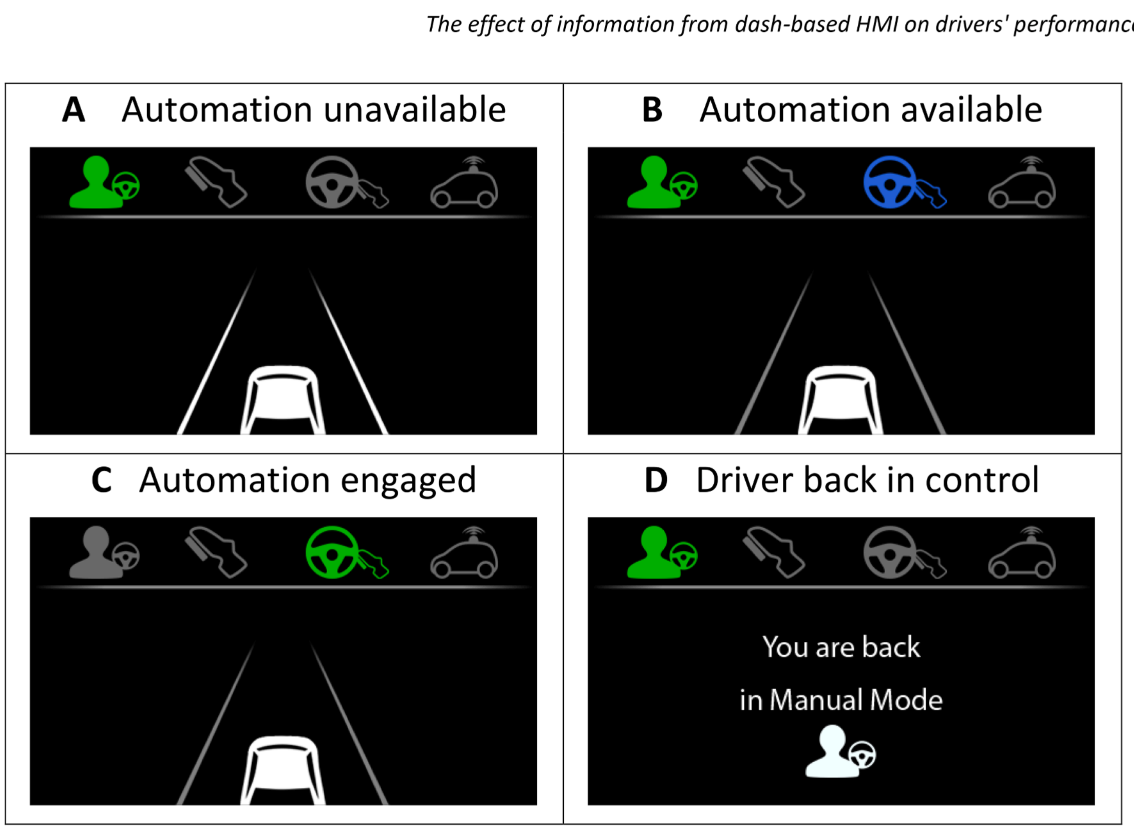

Fig. 3. Representation of the System HMI Condition (Designed in collaboration with CRF). (A) representation of the system in manual mode, with automation unavailable (grey steering wheel); (B) system in manual mode, with the automation available (blue steering wheel); (C) system in automation mode (green steering wheel), (D) message displayed after the driver resumes manual control. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Finally, the **Full HMI Condition** contained the same information presented in Fig. 3. However, when automation was engaged, additional information was presented to drivers about the surrounding traffic, including the lead vehicle's presence and the approaching vehicle in the adjacent lane (Fig. 4). Here, once the system perceived a vehicle ahead (6 s headway), a car symbol appeared on the HMI. When the ego vehicle started to brake to match the speed of the lead vehicle (at 2.8 s headway), a lane-change suggestion was triggered by displaying a green arrow, which was used to inform participants that it was safe to change lane, because the offside vehicle was not close enough to trigger a collision, if drivers wished to change lanes. The figure also shows a situation where there was a vehicle close by in the offside lane; however,

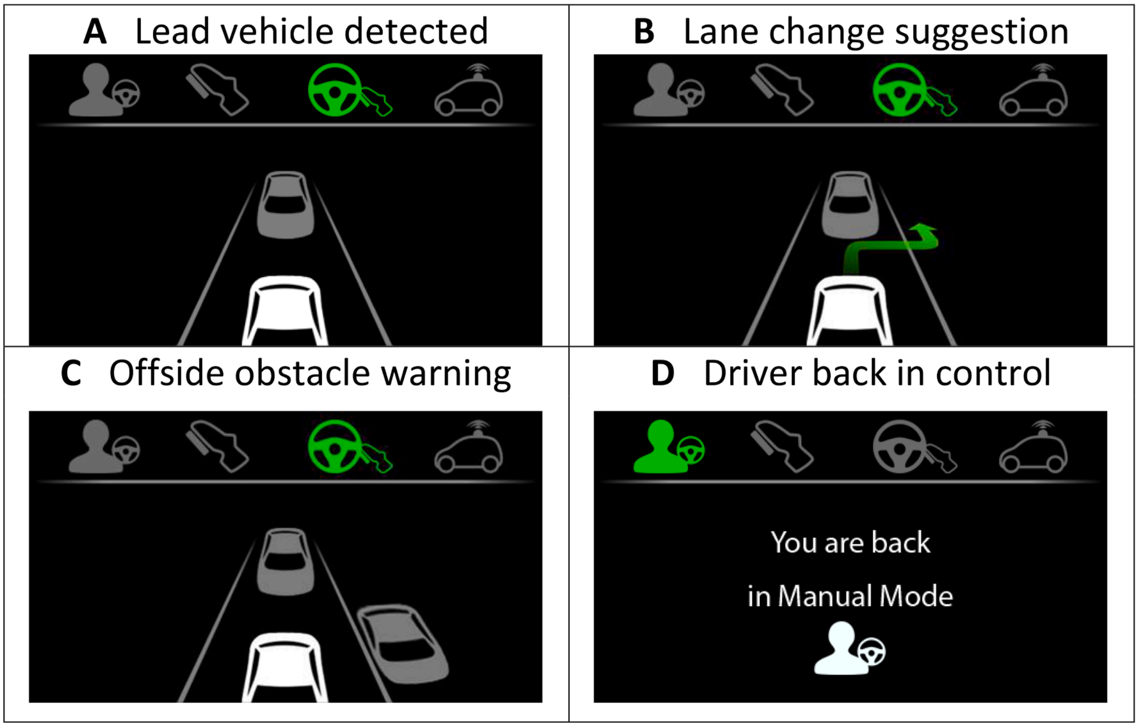

Fig. 4. Representation of the Full HMI Condition (Designed by: CRF). (A) represents the automation engaged, with a vehicle detected ahead; (B) represents the lane-change suggestion, whenever the system reached the designated distance to the vehicle in front; (C) represents the fake condition of the unsafe lane change, which was never present on the actual HMI (just on the briefing session) and (D) is the message confirming a successful transition of control.

this never happened during the experimental drives. We introduced this scenario as an illustration during the briefing session and encouraged drivers to judge for themselves whether it was safe to overtake the lead vehicle.

2.7. Non-Driving related task (NDRT)

Currently, L3 vehicle automation, as described by SAE (SAE, 2018), permits drivers to engage in other, non-driving related activities, but requires them to be ready to take control, when requested. Therefore, to understand how this ability to engage in other tasks during L3 automation affected lane-changing behaviour during a transition of control, drivers were asked to perform a non-driving related task (NDRT) as soon as the automated driving system was turned on. This visual secondary task, the Arrows task (adapted from Jamson & Merat, 2005), was displayed on a touchscreen monitor, placed near the gear selector, and involved presenting a series of arrows displayed on a 4 × 4 grid, as shown in Fig. 5. Drivers had to locate the one upward-facing arrow for each display and touch it as fast as they could. As soon as the up arrow was pressed, the next display appeared. If participants did not find an arrow within 5 s, a new 4 × 4 grid was displayed. To avoid interference with the HMI information, this version of the task was not accompanied by any auditory signals. To encourage driver engagement with the task, a “score to beat” was displayed on the screen, as shown in Fig. 5.

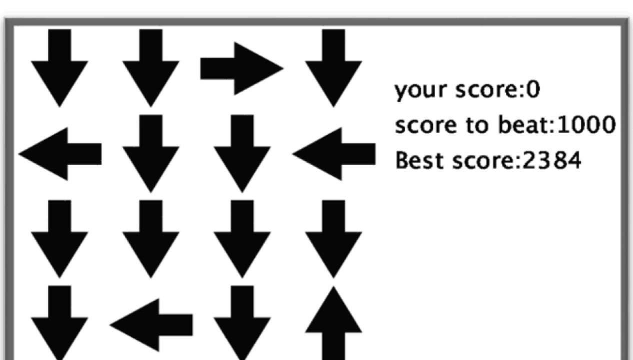

Fig. 5. Representation of the Arrows task, as it was displayed on the touchscreen near the gear stick.

2.8. Procedure

Upon arrival, participants were asked to read a description of the experiment and sign a consent form. They were then taken to the simulator dome and familiarised with the vehicle and its controls, including the HMI, and how to operate the automated system. During this briefing session, participants were given the opportunity to practice the Arrows task, both independently and during the automated drive. They were also informed that there was no takeover request, and that the ego vehicle would only brake/decelerate in the presence of a slower lead vehicle. Participants were instructed that, as soon as they felt the vehicle’s deceleration, and when they felt it was safe to do so, they should resume manual control of the vehicle, and try to perform a manual lane change to the offside (right) lane. As these were non-critical scenarios, there would be no collision if drivers did not resume manual control, and the vehicle maintained a maximum headway of 2 s, for as long as the automation was engaged. They were also instructed to reengage the automation and resume the Arrows task as soon as they had returned to the middle lane, after overtaking the lead vehicle.

After the briefing session, participants completed a 15-minute familiarisation drive, supervised by the experimenter. The familiarisation drive consisted of a short version of the experimental drives, with one lane-change scenario for each HMI. Once familiarised with the task and environment, the experimenter left the dome. The participants drove the three experimental drives, presented in a counterbalanced order, with five-minute breaks between each drive, during which participants left the simulator dome to reduce any fatigue effects.

2.9. Research variables

As described above, the independent variables were the three HMI conditions, and the distance of the vehicles in the offside lane during the lane-change scenarios (offside distance).

To measure how quickly drivers initiated a lane-change manoeuvre following a resumption of control, their Decision-Making Time (DMT) was calculated. This metric has been used in previous eye-tracking studies, to model human decision-making and performance (see examples in Ratcliff et al., 2016; Shaw, 1982; Krajbich et al., 2012, Forstmann et al., 2016). For this study, DMT was defined as the time between the beginning of drivers' disengagement from the NDRT to engage in the takeover process (t_{engage}) until the point they initiated the lane-change manoeuvre (t_{action}). t_{action} was also used during gaze behaviour analysis as an anchor point to define the time frame in which the eye movements were extracted from the raw experimental data.

During the data analysis process, we identified that, as it was a non-safety–critical scenario, there was a delay between the automated system's brake (signalising the presence of a lead vehicle to be overtaken) and drivers' interruption of the NDRT, since there was no time pressure for them to respond. It was also noted that not all drivers disengaged the automation in the same way (75% used the steering wheel, while 25% used the stalk). We also observed that some drivers disengaged the automation, but continued looking at the road environment before manually performing the lane-change manoeuvre. For this reason, there was no specific point in the experimental condition which could be used to measure t_{action} across all trials. Given the reasons presented above, a MATLAB (version R2016a, MathWorks, 2017) algorithm was developed to calculate drivers' DMT, based on a set of detection criteria, as follows:

- t_{engage} was calculated based on the moment drivers moved their head up from the arrows task display, immediately after the lead vehicle was detected by the automated controller ("A" in Fig. 2). The assumption for this detection criterion was that drivers stopped interacting with the NDRT after moving their head away from the display and started acquiring visual information to decide when to overtake the lead vehicle. Detection of drivers' head position (whether looking towards the NDRT or the road/HMI) was based on the eye-tracking system's gaze detection quality, since drivers' eyes were not trackable by the system while they performed the Arrows task.
- As the average steering wheel angle input during the manual sections of the experimental drives (outside the lane-change scenarios) was lower than 1° ($M = 0.64$, $SD = 0.14$), we assumed that any extreme value of steering wheel angle input after t_{engage} would signify the physical engagement with the lane-change manoeuvre. Further analysis found no cases in which drivers moved their steering wheel over 2° without fully committing to the lane-change manoeuvre. Based on this observation, t_{action} was calculated as the time as when drivers made the first steering wheel input over 2°, whether the automation was already disengaged, or not. Fig. 6 shows an example, for one participant, of how the DMT was calculated.
- The timings for DMT calculation were based on the simulator data output for all participants and trials, regardless of the method used to disengage automation or the experimental conditions. The sampling rate was 60 Hz.

The metric used to analyse drivers' gaze behaviour in the different test conditions (3xHMI and 3x offside distances) was the percentage of drivers' gazes towards five Areas of Interest (AoIs), during the 3 s that preceded t_{action}. This time window of 3 s was selected since not all drivers had the same DMT. Using a relative value for different time windows, would over/underestimate each individuals' gaze percentages, depending on the length of their DMT. A time window of 3 s was selected

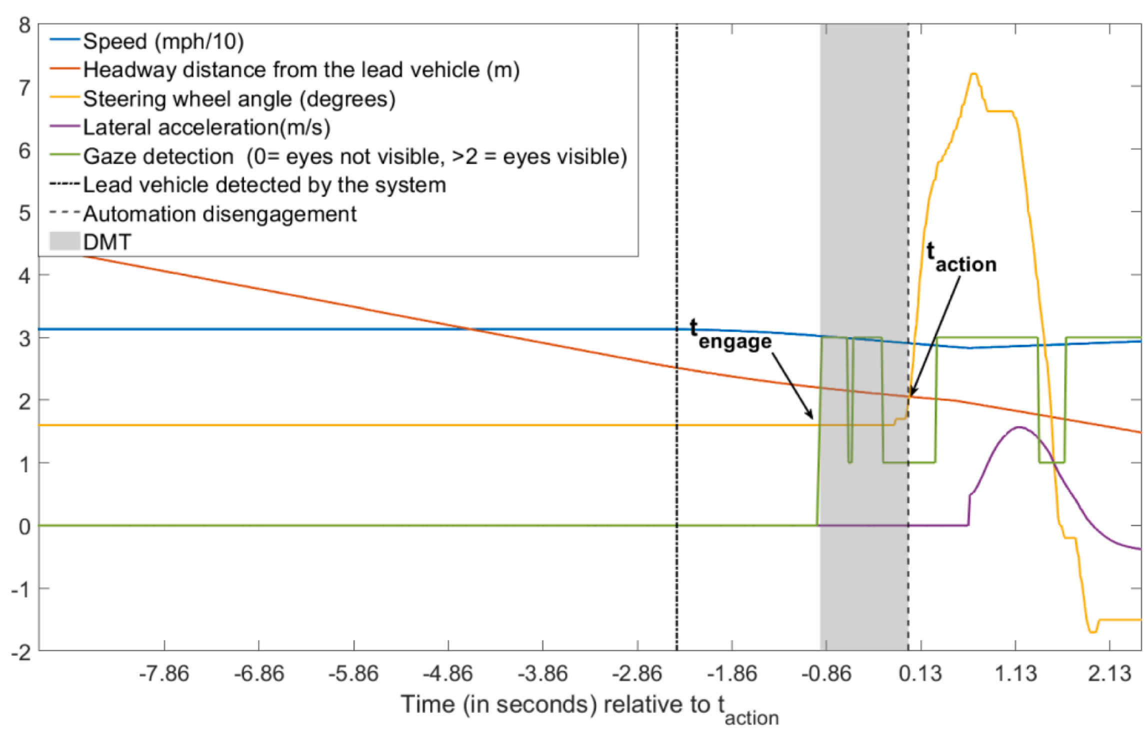

Fig. 6. Example of how Decision-Making Time (DMT) was calculated for a single participant. The green line (Gaze detection status) represented the detection of drivers' face in the eye-tracking system. We assumed that drivers were not looking to the road whenever the value in this variable was 0 (meaning drivers' head could not be detected). t_{engage} was detected whenever their gaze detection status was >=2 (meaning that the eye tracker could detect the participant's head, as they were looking upwards). The yellow line (steering wheel angle) was used to detect t_{action}, as it indicated when drivers were physically engaged with the driving task. The shaded grey area, between the defined points for t_{engage} and t_{action} is the total amount of the participant's DMT. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

as it included a complete DMT for 87% of participants, while minimising noise caused by non-trackable eye-tracking data (due to the NDRT). Decision-making models, such as those developed by Ali et al. (2019) also support our view that a 3 s time window is suitable to capture the decision-making process in a lane-change scenario.

Based on previous studies (Carsten et al., 2012, Louw et al., 2016; Louw et al., 2017; Louw & Merat, 2017; Louw et al., 2018), five separate regions were defined by the AoIs within the drivers' field of view (Fig. 7). The centre region was defined as a 6° circular area, centred on the mode of drivers' fixations (see Victor, 2005), defined during the first minute of their experimental drives, which was in manual mode. The other four regions were equally split between lateral and vertical sections of the screen (see Fig. 7 for a schematic representation of the AoI layout). The top and bottom of the centre region covered the road area beyond the lead vehicle, and the steering wheel/HMI area, respectively, and the two lateral regions covered the wing mirrors and adjacent lanes to the left and right of the central area.

A fixation was calculated as the persistence of drivers' gaze position in a 1° radial area, for at least 150 ms, consistent with the boundaries reported in the literature for dispersion-based fixation identification algorithms (see Salvucci & Goldberg, 2000; Nyström and Holmqvist, 2010). The analysis reported in this paper focused on three specific AoIs, as they were considered to be the most relevant for a lane-change manoeuvre, according to studies of eye-movements during lane changes (Tijerina et al., 2005; Doshi & Trivedi, 2009; Salvucci et al., 2001; Fitch and Hankey, 2012; Chovan, 1994). These were the centre, bottom and right AoIs.

2.10. Statistical analysis

The data was compiled and pre-processed using MatlabR2016a (MathWorks, 2017) and analysed using IBM SPSS v21 (IBM Corp, 2012). Further analyses were performed using the SKlearn tool in a Python environment (Python Software Foundation, 2020). A Kolmogorov-Smirnov test (Conover, 1999) was used to check for normality and showed that parts of the data had a slight positive skew. Whenever the data was found not to be normal, a logarithmic transformation was applied to rely on parametric tests for the statistical treatment. In cases where parametric tests were not possible, Friedman's test was used as a substitute for a two-way ANOVA. All figures presented are based on the untransformed data, with results based on tests performed on the transformed data.

To filter out the noise inherent in eye-tracking data, all gaze samples containing less than 75% of data points with "good gaze tracking quality", as specified by the eye-tracking software (no gaze estimation based on head position or missing data) were discarded. Two participants did not follow the instruction to perform the Arrows task, and spent the experimental drives looking towards the forward scene. Therefore, their data was not included in the analysis. To exclude other participants who did not adhere to the scenario instructions (e.g. did not perform the overtaking manoeuvre during the experimental drives), outliers were removed from the sample using a criterion of 3x interquartile range (IQR3). An α-value of 0.05 was used as the criterion for statistical significance, and partial eta-squared was computed as an effect size statistic. Where Mauchly's test indicated a violation of sphericity, degrees of freedom were Greenhouse-Geiser corrected.

2.11. Participants' Decision-Making time

To test whether the different information from the HMI, and the distance of the vehicles in the offside lane, affected participants' decision-making performance, a Friedman's test was conducted using drivers' Decision-Making Time (DMT), in seconds, as the dependent variable, while HMI condition (No HMI, System HMI, Full HMI) and Offside distance (100 m, 25 m, 15 m) were the independent variables.

Friedman's test results found significant differences between drivers' DMT, based on the HMI condition, and offside distance, during the moment of the takeover [$\chi2(8) = 15.025$, $p = 0.05$]. Individual Kruskal-Wallis *post-hoc* tests showed a significant effect of offside distance [$\chi^2(2) = 0.953$, $p = 0.0387$], with higher mean DMT values associated with shorter offside distances (15 m = 3.09 s, 25 m = 2.49 s, 100 m = 1.83 s). However, the three HMI conditions were not found to affect this value [$\chi^2(2) = 2.65$, $p = 0.261$]. As shown in Fig. 8, drivers' DMT was longer when the vehicle in the offside lane was closer, with a similar pattern observed regardless of the level of information from the HMI.

2.12. Participants' gaze distribution

Fig. 9 shows the proportion of drivers' raw gaze to the different AoIs (see Fig. 7), for the 3 s before and 5 s after t_{action}. This visualisation shows a similar gaze pattern for the three HMI conditions, after the resumption of control. However, many more glances are seen to the HMI (bottom

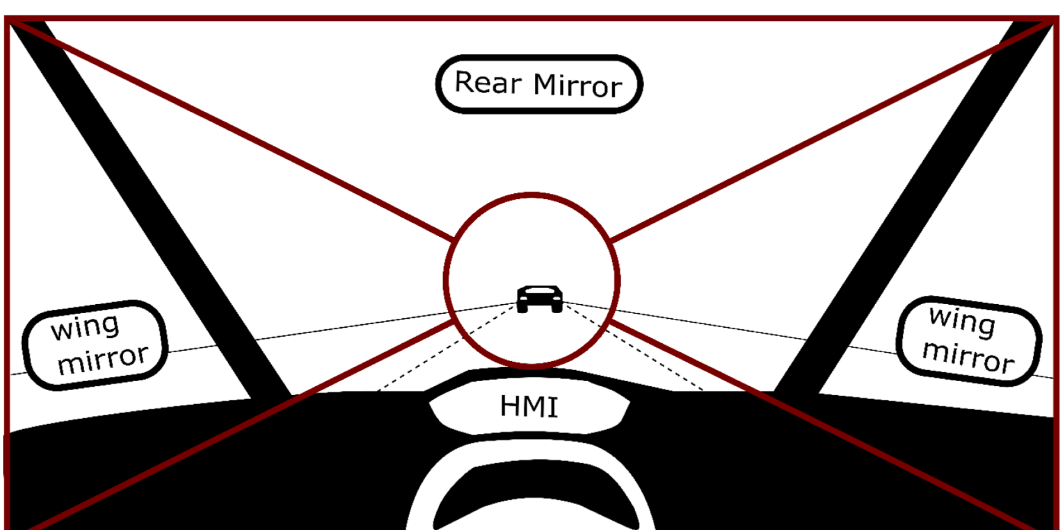

Fig. 7. Schematic representation of the division of AoIs used in the analysis of drivers' eye movements. The red markings represent the AoIs mentioned above. The black/white drawings represent the visual elements present in the area covered by each of the AoIs. Note that this is just a schematic representation and is not a precise depiction of the elements in the real simulator dome. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

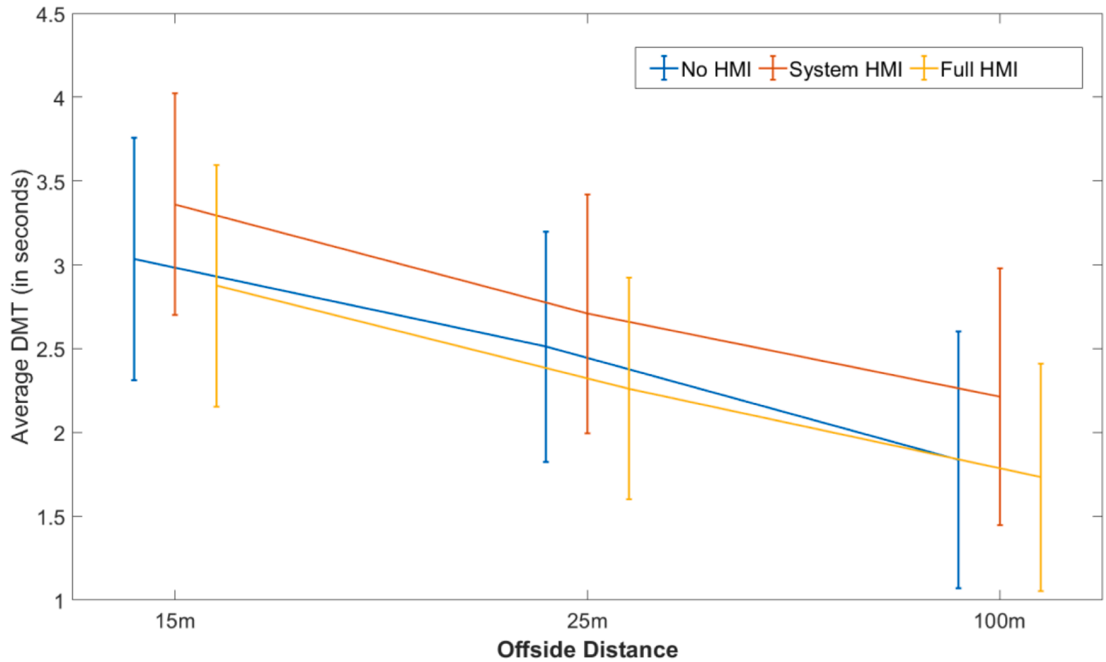

Fig. 8. Results of Friedman's test on drivers' Decision-Making Time in different test conditions.

AoI) when the automation was engaged in the Full HMI condition.

As can be seen in Fig. 9, for all three HMI conditions, there is a sharp decrease in "Gaze not Tracked" data points during the 3 s before t_{action}. As drivers' exact gaze was not trackable during the execution of the NDRT, it is assumed that this large grey area represents the percentage of drivers looking downwards to the Arrows task display.

In terms of percentage of gaze distribution, the pattern roughly follows that observed for manual lane changes (Salvucci et al., 2001; Tijerina et al., 2005). During the time before t_{action}, which can be associated with what Tijerina et al. (2005) describe as the "decision-making phase", drivers distributed their gaze mainly between the centre (orange) and right (light blue) AoIs, suggesting they were mostly paying attention to the offside lane, and the vehicle ahead, probably to judge whether or not it was safe to engage in the lane-change manoeuvre. After t_{action} ("action phase", Tijerina et al., 2005) a gradual reduction in the percentage of gazes to the right AoI, and an increase in the percentage of gazes to the centre is seen for all HMI conditions, suggesting that drivers were focusing on the vehicle's heading, to manually execute the desired manoeuvre, and change lanes.

To measure the effect of the HMI information, and traffic densities, on drivers' gaze behaviour, three 3X3 ANOVAs were conducted, one for each of the main AoIs of interest: centre, right and bottom. Each ANOVA had HMI condition (no HMI, system HMI, full HMI) and Offside distance (100 m, 25 m, 15 m) as independent variables, and the percentage of drivers' gaze to the respective AoI, during the 3 s which preceded t_{action} as the dependent variable (Fig. 10).

There was a main effect of HMI condition on the percentage of gaze to the centre AoI [$F(2, 258) = 6.886$, $p = .001$, $\eta_p^2 = 0.051$], where *post-hoc* Bonferroni tests showed this value to be significantly lower during the full HMI condition, compared to the other two conditions. There was also a main effect of offside distance [$F(2, 258) = 3.458$, $p = .033$, $\eta_p^2 = 0.026$], where drivers' gaze to the centre AoI was higher during the shorter gap condition (15 m). No significant interactions were found F (2, 258) = 0.810, $p = .520$, $\eta_p^2 = 0.012$].

The ANOVA results for the percentage of gaze to the right AoI showed a main effect of offside distance [$F(2, 258) = 4.825$, $p = .009$, $\eta_p^2 = 0.036$], with a higher proportion of gaze towards the right during the shorter gap conditions (mean = 17.4%, 16.5% and 10.8%, respectively, for the 15 m, 25 m and 100 m, conditions). However, there was no significant effect of HMI condition on gaze to the right, [F (2,258) = 0.038, $p = .195$, $\eta_p^2 = 013$], and no significant interaction between HMI condition and offside distance [$F(4, 258) = 0.023$, $p = .681$, $\eta_p^2 = 0.010$].

Finally, there was a significant effect of HMI condition on gaze towards the bottom AoI [$F(2, 258) = 18.852$, $p < .001$, $\eta_p^2 = 0.126$], with a significantly higher proportion of gaze towards the bottom as the amount of information from the HMI increased (Full HMI > System HMI > No HMI). There was no significant main effect of offside distance [F(2, 258) = 0.586, $p = .588$, $\eta_p^2 = 0.005$], and no interaction effects [F(4, 258) = 1.587, $p = .119$, $\eta_p^2 = 0.028$].

2.13. Gaze behaviour and DMT correlation

As previous literature shows a link between gaze behaviour and the decision-making process (Orquin and Mueller Loose, 2013), we investigated how individual differences in gaze concentration to different AoIs affected participants' lane changing DMT, by using a regression model to correlate drivers' DMT with 20 different measures of drivers' gaze behaviour, extracted from the same period of time for which the DMT was calculated (from t_{engage} to t_{action}). These included, the percentage of raw gaze; fixation count; average fixation duration; and time of first fixation, for each AoI. The model also considered the lane-change order (1 to 6) as an independent variable, to account for learning effects.

As the regression contained many predictor variables, and the type of correlation between the model's elements was unknown, we used a random forest (see Segal, 2003; James et al., 2000) machine-learning algorithm for the data fitting. To identify which measures from drivers' gaze behaviour were correlated with their DMT, separate models were created for each of the HMI conditions, and the predictor weight values of each variable (measures) were used as a proxy for the importance of the information located in the AoI for drivers' decision-making process. The data was split in a 75:25 ratio between training and validation of the models, and the input parameters were tested repeatedly, aiming to reach a better model accuracy. Variables with less than 1% (0.01) predictor weight were discarded. To optimize the model output, the hyperparameters (number of variables sampled on each

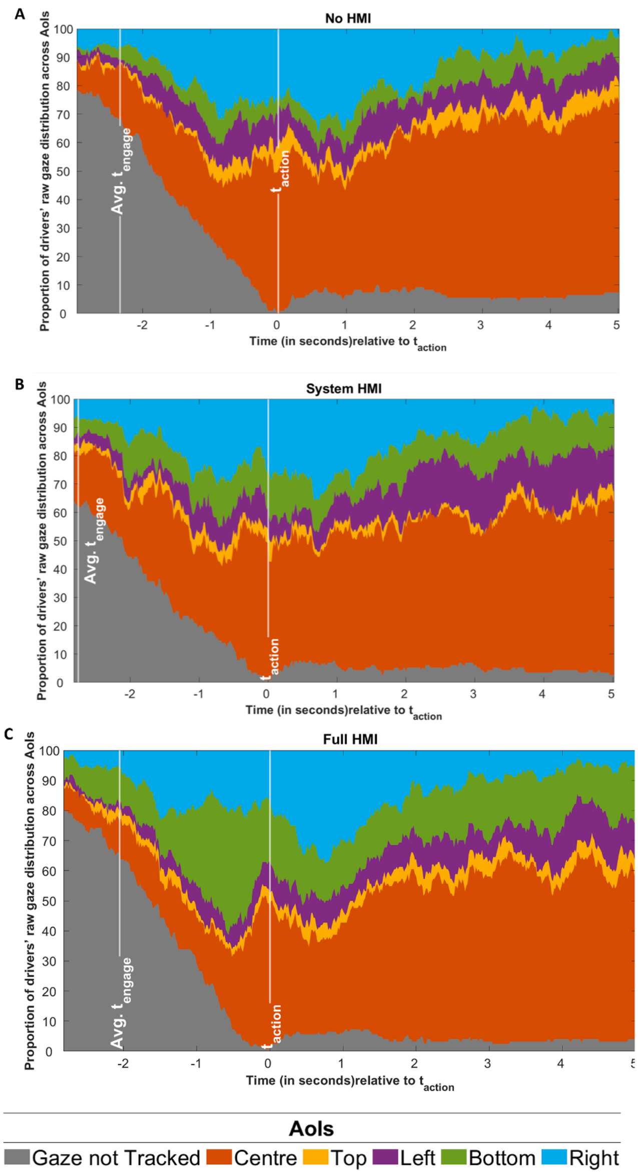

Fig. 9. Drivers' gaze distribution across the five AoIs. The X-axis represents the 3 s before and 5 s after t_{action}. The Y-axis shows the percentage of drivers gazing towards each AoI, in a given point in time. The data was captured at a sampling rate of 60 Hz. As participants' eyes were not trackable during the Arrows task, all the data points collected during this time on the task were captured as "Gaze not Tracked".

branch of the tree, and number of trees to grow) of the random forest algorithm, were tested using a grid search, and only the combinations of hyperparameters that yielded the best accuracy are reported in this paper.

Results showed that the only statistically significant variable as predictor of DMT (i.e. above 0.01 predictor weight value) was the percentage of raw gaze towards the five different AoIs. As the order in which the events were presented to the driver (1–6) had no importance as a predictor, we assumed no learning effects in the decision-making process. Table 1 contains the three regression model outputs that yielded the best results, in terms of fitting, for their respective experimental conditions. All the regression models had relatively high accuracy (approx. 70%) given the dataset's size, and an average error (ranging from 0.27 s to 0.31 s, in a task with an average duration of 2.47 s), within the boundaries of expected inherent variance in lane-change behaviour data (see Arbis & Dixit, 2019), suggesting that the model is capable of predicting drivers' DMT reliably, based on their gaze.

For the No HMI, and System HMI conditions, as expected, the most important variables extracted from drivers' gaze behaviour for predicting their DMT in lane-change scenarios were the percentage of gaze to the mirrors and offside lanes (right AoI) and the road centre (centre AoI). Our data suggests that drivers who focussed on those two main points of the road environment were more likely to make significantly quicker decisions and responses, than those who deviated their gaze to less important areas, such as the top and bottom AoIs.

On the other hand, the observed changes in the predictor weight values for the Full HMI condition suggest that the addition of the advisory green arrows, indicating it was safe to change lanes, affected how drivers divided their attention between the different regions, when more advice was available from the HMI. In this condition, the percentage of gaze towards the bottom AoI gains importance (weight value = 0.27, compared to ~ 0.02 for the other two conditions), over the percentage of gaze to the centre AoI (weight value = 0.13, compared to 0.38 for the other two conditions), becoming the second most important predictor.

3. Discussion

The objective of this study was to measure the effect of different types of HMI information, and guidance, on drivers' gaze behaviour and decision-making time, during transitions of control from automation, which occurred prior to a lane-change manoeuvre. The level of traffic density in the offside lane was also manipulated to understand how drivers used different sources of information from an HMI and the road environment, to help with more challenging lane-changing decisions, when traffic behaviour was more ambigious. A series of regression models were also generated to correlate drivers' gaze behaviour to the decision-making time.

3.1. The effect of dash-based information on drivers' gaze behaviour

Results from drivers' gaze concentration to the different AoIs illustrated a higher percentage of gaze towards the bottom AoI, corresponding directly to the amount of information presented on the HMI, at the expense of reduced gaze to the road centre (centre AoI). In the Full HMI condition, gaze towards the bottom AoI (HMI) increased just before drivers' first steering wheel input (t_{action}), which was immediately before drivers started to change lanes, suggesting that drivers used information from the HMI to help them decide how to act (at least for the Full HMI condition), at the expense of glances to the centre AoI (road centre). This finding is supported by core gaze and decision-making theory (Carrasco, 2011; Orquin and Mueller Loose, 2013; Sullivan et al., 2012), which states that humans tend to fixate longer on the information that they are processing. This finding highlights one potential issue with the implementation of overly-informative and complex HMIs, as drivers attend to information presented on an HMI, as a trade-off to glances to the road centre. This issue must be taken into account when designing future vehicle HMIs, because reduced glance time to the road is generally associated with higher crash probabilities (see Harbluk et al. 2007). Of course, these results may also be affected by the novelty of the messages used in this study, and it is important to understand how such gaze patterns might change with longer term use of such in-vehicle systems and interfaces.

Drivers' gaze pattern towards the HMI was not found to be affected by the position of vehicles in the offside lane. This result was not expected, and goes against our initial hypothesis that drivers would rely more on the HMI information, when the scenario was associated with more difficult decisions, e.g. when the vehicle in the offside lane was closer. A look at drivers' attendance to the side mirrors explains this further, showing a significant increase in the percentage of drivers' gaze towards the right AoI, for shorter offside distances. This finding suggests that, for safety critical situations, drivers relied also on their own

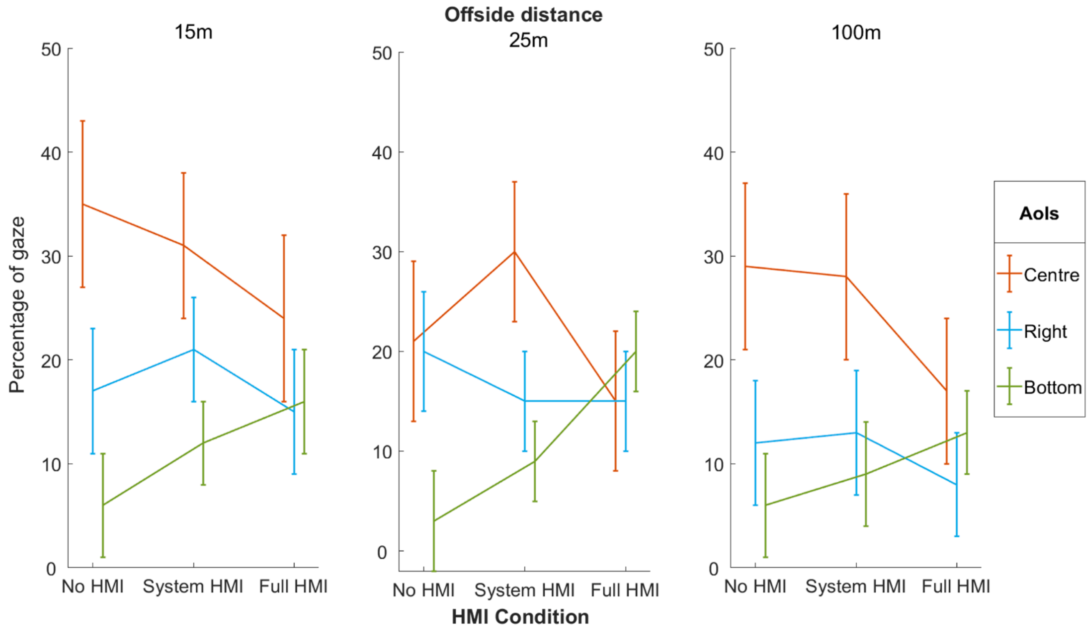

Fig. 10. Results for the 3 ANOVA tests performed on drivers' gaze on each AoI during the 3 s that preceded t_{action}.

Table 1
Model performance output and weight values for regression for each HMI condition. The first five lines represent the weight values for the predictor variables (all weights were positive values, and their sum should always total 1). The model accuracy is based on the training dataset, and the values of the average prediction errors are based on the validation dataset. T underlined number in the Full HMI column is highlighted to emphasize the significant difference in this model's output when compared to the other two.

Model variables		No HMI	System HMI	Full HMI
Gaze percentage on AoI during DMT	Right	0.5	0.5	0.55
	Centre	0.38	0.38	0.13
	Left	~0.09	~0.09	0.05
	Bottom	~0.02	~0.02	*0.27*
	Top	~0.01	~0.01	~0.0
Model accuracy		59.15 %	72.69 %	75.29 %
Avg. prediction error		0.27 s	0.3 s	0.31 s

judgement, on top of the HMI advice. The increased proportion of gaze towards the mirrors for more difficult decisions was expected, and is in line with previous studies (Orquin and Mueller Loose, 2013; Sullivan et al., 2012), suggesting that real-time information from the surrounding road environment is more valuable to drivers in more safety critical situations. Since we did not find any difference in the pattern of drivers' gaze to the right AoI (right mirror), across the three HMI conditions, our results suggest that drivers did not use the HMI information as a substitute for the mirror checks, which is typical for a manual lane-change (Tijerina et al., 2005), but rather a complement to it, since both glances to the right and to the HMI were constantly present for the events in the Full HMI and System HMI conditions.

In terms of our regression model, "glances to the right AoI" was found to be the only predictor variable in the Full HMI condition, showing stronger correlation with drivers' DMT than the "glances to the HMI" variable. The suggestion that glances to the side mirrors is the most important predictor of drivers' decision for a lane-change prediction model is consistent with studies on lane changes in manual driving (Doshi & Trivedi, 2009; Salvucci et al., 2001), and highlights the relevance of mirror checks for the decision-making process, even in automated driving scenarios. This similarity in gaze behaviour between automated and manual lane changing was also observed in another lane-changing study conducted in our lab, which did not include different types of information on the HMI (Gonçalves et al., 2020), and supports the argument that drivers tend to rely on information from the road environment, for their decision-making.

Of course, it can also be argued that this mirror-checking pattern illustrates a potential lack of trust in the automated driving system, and our HMI information (Lee & See, 2004), or is due to an automatised, well-learnt, behaviour. It is reasonable to assume that such patterns of behaviour may change after prolonged exposure to a reliable automated system and HMI (i.e. a conditioned learned behaviour, Charlton & Starkey, 2011). Further work is, therefore, needed to observe how prolonged and sustained interaction with such in-vehicle HMIs changes the long-term behaviour of drivers, and their gaze patterns, and how different levels of system reliability and traffic scenarios affect this behaviour.

3.2. The effect of dash-based information on drivers' DMT

Drivers' DMT was found to increase in line with the position of the vehicle in the offside lane, with higher DMTs for closer vehicles. This result was expected, and is supports the large body of literature on decision-making theory (Shaw, 1982; Ratcliff et al., 2016), and lane-change manoeuvres (Gipps, 1986, Arbis & Dixit, 2019). Here, the uncertainty associated with a lane-change ahead of a nearby vehicle in the adjacent lane caused drivers to spend longer making a lane-change decision, likely associated with the need to look around more at their surrounding environment. However, the lack of an effect of HMI condition on drivers' DMT goes against results from other experiments in the field of vehicle automation (Richardson et al., 2018; Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2017; Stockert et al., 2015), which suggest a significant improvement in drivers' performance, with the help of information from the HMI.

This observed lack of a difference for the DMT values for different HMI conditions in this study may be due to our HMI design, which was perhaps not as informative for participants as we had envisaged. On the other hand, the output of our regression models showed that, in the Full HMI condition, there was a strong correlation between "glances to the HMI" and drivers' DMT. This was not the case for the other two HMI conditions, suggesting that the presence of supportive information (i.e. the green arrow signalling a safe lane change) is indeed beneficial for the decision process (supporting the findings from Richardson et al., 2018; Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2017, Stockert et al., 2015). However, the observed correlation was not strong enough to generate perceivable changes to the mean DMT, based on the experimental conditions alone, as individual differences in drivers' gaze behaviour might have affected the way drivers interacted with the visual information, and therefore, masking the potential effects on their DMT.

The arguments in favour of a more informative/supportive HMI is that a clearer and more direct orientation to the situation, as provided by the HMI, helps the driver to recover situation awareness, and avoid potential accidents caused by delayed or inappropriate responses. However, drivers in the current study were not under pressure to perform a lane-change as quickly as they could (i.e. they were asked to complete a discretionary lane-change). Results from Ali et al. (2020) demonstrated that drivers tend to spend more time, and are more careful in their lane-changes, when there is more information from a vehicle HMI. According to these authors, drivers changed the way they accessed the information, not only checking the mirror and the road centre, but scanning all the information at their disposal. Regarding the current study, this suggests that our drivers may have checked the HMI as a routine, as they expected the information to be there, but also checked the side mirrors, as they are habitually used to, before a lane-change. Therefore, the contributions from the HMI information to drivers' DMT were likely countered by the fact that drivers spent more time to check and process the additional information on the HMI, on top of their standard gaze check routine, which ultimately increased their DMT.

4. Conclusion

The data presented here offers new insights for the design of new in-vehicle HMI relevant to automation. Although additional information from such HMI should provide potential supporting benefits, results from this study suggest that excessive HMI information comes at a cost, by attracting drivers' gaze, at the expense of glances to the road environment. Results suggest that although drivers looked at the HMI on the run up to a lane change, they ultimately opted to also "believe their own eyes" and use information from the driving environment to decide when to change lane, looking consistently more at the side mirrors, just before the changing lane, regardless of the HMI condition. Therefore, system designers must be aware that not all information presented on an HMI is a good substitute for that provided by the surrounding environment. Further research is needed to understand what type of information from an HMI is useful (e.g. indicating system status) versus those that are considered superfluous. The value of using other modalities for presentation of relevant information in such scenarios should also be explored. This includes the use of heads-up displays, or spatially congruent haptic messages (Ho et al., 2006), which would allow the system to provide supportive information, without compromising drivers' visual attendance to the road environment.

Regarding limitations of this work, and considerations for future studies, the accuracy of the regression models' output (59.15 % – 75.29%) is clearly limited by the overall sample size of the data, which might compromise the takeaway implications of such analysis. This work has also not considered the importance of other factors known to affect the overall takeover process and decision to change lanes, such as driver experience, trust in vehicle automation technology, and fatigue, as examples. Finally, the lack of agreement between the results from this study, and those of others in this context (e.g. Naujoks et al., 2017), may be due to a lack of time pressure for drivers in the current study, or the use of rather simple messages from our HMI. Further work should, therefore, consider the use of a more informative interface, or a more challenging decision task, to assess the value of such information to drivers.

CRediT authorship contribution statement

Rafael C. Gonçalves: Conceptualization, Software, Formal analysis, Writing – original draft, Visualization. **Tyron L. Louw:** Methodology, Validation, Investigation, Writing – review & editing, Supervision. **Ruth Madigan:** Validation, Investigation, Writing – review & editing. **Manuela Quaresma:** Validation, Writing – review & editing. **Richard Romano:** Validation, Writing – review & editing. **Natasha Merat:** Methodology, Validation, Writing – review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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